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Low Carbon Multi-Objective Unit Commitment Integrating Renewable Generations

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ABSTRACT Unit commitment is an intractable issue aiming to reduce the overall economic cost of power system operation while maintaining the system constraints. Due to the emerging scenario of global warming, many countries are vigorously developing renewable energy to replace the traditional fossil power plant, in order to reduce the environmental and carbon emission. The increasing penetration of renewable generation significantly challenge the economic and security of power system operation. In this paper, a low carbon multi-objective objective unit commitment model considering economic cost, environmental cost and, more importantly, the carbon emission is established, integrating wind and solar power and therefore generating a multi-objective, high-dimensional, strong non-linear, multi-constraint and mixed integer optimization problem. The non-dominated sorting genetic algorithm-III is tailored and adopted for solving the proposed challenging task, where the decision-making scheme is designed according to the normalization method and weighted sum function. Numerical results show that the proposed complex many-objective low carbon unit commitment model can be successfully solved by the proposed algorithm and the carbon emission is effectively reduced by the integration of renewable generations.

INDEX TERMS NSGA-III, multi-objective, unit commitment, wind power, solar power.

I. INTRODUCTION

Electrical power is the fundamental element for the economic development and normal life. With the rapid development of the world economy, the demand for electrical energy is continuously increasing, leading to a large amount of fossil energy consumption and increasingly prominent global warming and environmental pollution problems. Wind and solar power are the most mature and developed energy resources. They both have the advantages of clean and pollution-free and abundant reserves, playing significant roles in reducing environmental pollution and promoting sustainable development. The large penetration of the both renewable resources is the ultimated approach in achieving the low carbon energy future. However, the strong intermittent renewable generation strongly challenges the current power system operation.

Unit commitment is the fundamental task of power system operation, where economic cost is often considered as the key objective. In solving the UC optimization problem, a number of algorithms have been proposed and adopted. Featured conventional approaches involve dynamic programming (DP) [1], mixed-integer linear programming (MILP) [2] and Lagrangian relaxation (LR) [3]. Su *et al.* used fuzzy set notations in DP making no errors in forecast loads [4]. Long proposed a approximate DP to solve large-scale UC problem [5]. With the problem becomes increasingly complex, DP suffers the "dimensionality disaster" problem. Moralesespana *et al.* proposed a tight and compact MILP and improve the speed of optimization [6]. Venkatesh *et al.* analyzed the solution

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of wind power penetrating in power system with MILP [7]. Peterson *et al.* used LR to solve UC problem considering the constraints of unit climbing rate [8]. In addition to the conventional programming based approaches, many scholars have applied heuristic algorithms to UC problem. Some common heuristic algorithms such as genetic algorithm (GA) [9], gravitational search algorithm (GSA) [10], particle swarm optimization (PSO) [11] and etc. Kazarlis *et al.* firstly presented a GA solution to the UC problem [12]. Jo *et al.* used an improved GA considering the uncertainty of power sources [13]. Roy and Kumar proposed GSA to optimize UC problem [14]. ElAzab *et al.* used GSA to reduce the incorporated cost for UC integrating plug-in electric vehicles [15]. Raglend *et al.* proposed PSO to solve profit based UC problem [16].Kamboj *et al.* proposed a hybrid PSO-GWO (Grey Wolf Optimizer) approach for UC and obtain better results than classical PSO [17]. Simopoulos *et al.* use simulated annealing in unit commitment considering reliability [18]. Sundaram *et al.* integrate artificial bee colony algorithm and tabu search to solve the profit-based unit commitment problem [19]. Marrouchi *et al.* apply fuzzy logic approaches in unit commitment compared with gradient-genetic algorithm to test their performance [20]. Chen *et al.* integrate expert system with elite particle swarm optimization to form a two-level hierarchical approach for the unit commitment problem [21].

To integrate renewable energies in UC, researchers have also paid significant attentions. Ji *et al.* proposed an improved GSA for UC integrating wind power [22]. Quan *et al.* proposed a comprehensive computational framework and a new scenario generation method for renewable energy [23]. Lorca and Andy proposed a new multistage adaptive robust optimization model considering large-scale wind and solar power [24]. Cordova *et al.* proposed an efficient forecasting-optimization scheme considering the challenge large-scale wind and solar power integrated to power systems [25]. Xu *et al.* developed a stochastic two-stage day-ahead UC model and a new economic dispatch model integrating solar and wind resources [26]. Cui *et al.* analyzed the relationship between reliability and solar power forecasting improvements [27]. Wu *et al.* proposed a systematic framework that quantified the integration costs considering solar photovoltaic power [28]. Hao *et al.* made a comparative study on uncertainties of renewable energy integrated to the power system [29].

Apart from the economic cost, environmental and carbon emission issues are important to the power system. Many scholars have conducted researches in modeling multi-objective multi-constrained nonlinear UC problems. Wu *et al.* proposed a multi-objective self-adaptive differential evolution (MOSADE) algorithm to optimize fuel consumption and emissions [30]. Elsied *et al.* [31] proposed a real-time energy management system that uses binary particle swarm optimization (BPSO) to minimize energy consumption, CO_2 emission and other pollutant emission. Lokeshgupta *et al.* [32] used multi-objective particle swarm optimization (MOPSO) to minimize the dynamic economic and emission dispatch problem of the system. Chandrasekaran and Simon employed artificial bee colony algorithm on three conflicting functions, fuel cost, emission and reliability level [33]. Li *et al.* combined NSGA-II and a local search algorithm to minimize the operation cost and emissions [34]. Furukakoi *et al.* used the stochastic programming algorithm to minimize the PV output prediction error and improve voltage stability [35].

In this paper, non-dominated sorting genetic algorithm-III (NSGA-III) [36], [37] is used for the unit commitment problem integrating wind and solar power considering economic cost, CO_2 and environmental emission. NSGA-III is one of the most popular multi-objective genetic algorithms, which can reduce the complexity of non-dominated sorting genetic algorithm. It has the advantages of fast running speed, quickly converging speed, which makes it become the basis of other multi-objective optimization algorithms. The key contributions including three aspects are as follows:

(1) A novel low carbon multi-objective unit commitment (LCMOUC) problem is modeled in the paper, comprehensively considering economic cost, CO_2 emissions and sulfur pollutant emissions, which can heavily reduce the carbon emission of the power system.

(2) Wind and solar power generation is integrated into the LCMOUC problem formulation to verify their low-carbon impact.

(3) NSGA-III method is adopted and tailored in optimizing the proposed model compared with other multi-objective algorithms to demonstrate its optimization superiority.

The remainder of this paper is organized as follows: the problem formulation of LCMOUC is discussed in Section II, followed by the proposed NSGA-III based optimization method for solving LCMOUC is demonstrated in Section III. Experimental results and case studies LCMOUC problem are presented in Section IV. Finally, Section V concludes the paper.

II. PROBLEM FORMULATION

A. OBJECTIVE FUNCTION

In this section, the proposed LCMOUC problem is formulated. The objectives of the problem include economic cost $f1$, CO_2 emissions $f2$ and sulfur pollutant emissions $f3$, among which the carbon emission is accounted by the CO_2 amounts. For all these three objectives, with the economic cost increasing, the pollutant emissions will decrease at the same time, which shows the conflict between these objectives.

$f1$:The economic cost F_ec contains fossil fuel cost and start-up cost which are showed as follows:

$$min\ F_ec = \sum_{t=1}^{T}\sum_{j=1}^{n}[F^f_{j,t}(P_{j,t}) * I_{j,t} + SUC_{j,t} * (1 - I_{j,t-1}) * I_{j,t}] \quad (1)$$

where n is the total number of units, T represents the time periods, $F^f_{j,t}$ is the fuel cost of the j-th unit at time t, $P_{j,t}$ is the power of the j-th unit at time t, $I_{j,t}$ is the binary symbol representing the on/off-line status of units, where 1 represents the on-line status of units and 0 represents the off-line status of units, $SUC_{j,t}$ is the start-up cost of the j-th unit at time t.

The fuel cost of the j-th unit can be defined as follows:

$$F_j^f(P_{j,t}) = a_j + b_j * P_{j,t} + c_j * P_{j,t}^2 \tag{2}$$

where a_j, b_j and c_j are the corresponding coefficients of each unit.

The start-up cost of the j-th unit can be defined as follows:

$$SUC_{j,t} = \begin{cases} SUC_{H,j} & MD_j \leq T_{j,t}^{OFF} \leq MD_j + T_{cold,j} \\ SUC_{C,j} & T_{j,t}^{OFF} > MD_j + T_{cold,j} \end{cases} \tag{3}$$

where $SUC_{H,j}$ is the hot-start cost and $SUC_{C,j}$ is the cold-start cost, MD_j is the minimum down time, $T_{j,t}^{OFF}$ is the off-line duration time and $T_{cold,j}$ represents the cold-start hour.

$f2$: CO_2 pollutant emissions is denoted as:

$$CO2_e = \sum_{t=1}^{T}\sum_{j=1}^{n}[F_{j,t}^c(P_{j,t}) * I_{j,t}] \tag{4}$$

$$F_{j,t}^c(P_{j,t}) = \alpha_{c,j} + \beta_{c,j} * P_{j,t} + \gamma_{c,j} * P_{j,t}^2 \tag{5}$$

where $F_{j,t}^c(P_{j,t})$ represents the emission amount, $\alpha_{c,j}$, $\beta_{c,j}$ *and* $\gamma_{c,j}$ are CO_2 emission coefficients.

$f3$:Sulfur pollutant emissions is denoted as:

$$S_e = \sum_{t=1}^{T}\sum_{j=1}^{n}[F_{j,t}^s(P_{j,t}) * I_{j,t}] \tag{6}$$

$$F_{j,t}^e(P_{j,t}) = \alpha_{s,j} + \beta_{s,j} * P_{j,t} + \gamma_{s,j} * P_{j,t}^2 \tag{7}$$

where $F_{j,t}^s(P_{j,t})$ represents the emission amount, $\alpha_{s,j}$, $\beta_{s,j}$ *and* $\gamma_{s,j}$ are sulfur emission coefficients.

B. CONSTRAINTS

The constraints corresponding to the objectives are showed below:

1) Power balance limit at time t:

In actual power system, the power generation should be equal to the load demand all the time, which is an arduous task and can be showed as follows:

$$\sum_{j=1}^{n} P_{j,t} * I_{j,t} + P_{wind,t} + P_{solar,t} = P_{D,t} \tag{8}$$

$P_{wind,t}$ and $P_{solar,t}$ represent the wind and solar power respectively, and $P_{D,t}$ is the predicted power demand.

2) Power reserve limit at time t:

The spinning reverses should be considered for the unexpected extra load demand, which can be formulated as follows:

$$\begin{cases} \sum_{j=1}^{n} P_{j,max} * I_{j,t} + P_{wind,t} + P_{solar,t} \geq P_{D,t} + SR_t \\ \sum_{j=1}^{n} P_{j,min} * I_{j,t} + P_{wind,t} + P_{solar,t} \leq P_{D,t} + SR_t \end{cases} \tag{9}$$

where SR_t is the reserved power, $P_{j,min}$ and $P_{j,max}$ are the minimum and maximum power of the j-th unit respectively.

3) Minimum on/off-line time limit of the j-th unit:

The status of the units in power system can only be on-line or off-line, which is related to the minimum up and down time of the unit.

$$I_{j,t} = \begin{cases} 1 & 1 \leq T_{j,t}^{ON} < MU_j \\ 0 & 1 \leq T_{j,t}^{OFF} < MD_j \\ 0 or 1 & otherwise \end{cases} \tag{10}$$

where $T_{j,t}^{ON}$ is the on-line duration time at time t, MU_j is the minimum up time.

4) Power limit of the j-th unit:

The generation capacity limits the power of the corresponding unit to a certain range, which can be shown as follows:

$$P_{j,min} * I_{j,t} \leq P_{j,t} \leq P_{j,max} * I_{j,t} \tag{11}$$

III. NON-DOMINATED SORTING GENETIC ALGORITHM-III

The NSGA-III method is the predecessor of the well known NSGA-II and has shown advantage in addressing the problem with many objectives when dominated particles are difficult to figure out [36], [37]. The main idea of NSGA-III is to use elite strategies to retain excellent individuals to the next generation and avoid the loss of excellent individuals. More importantly, the strategy based on the reference points is used to select excellent individuals, and the algorithm has a better global search ability in handling multi-objective optimization problems. The procedure of NSGA-III is showed at Figure. 1.

The procedure of NSGA-III is similar to NSGA-II, and the selection mechanism for maintaining diversity of the population changes from the crowding comparison operator to an selection mechanism based on reference points. The individual selection mechanism of NSGA-III is showed as follows.

A. NON-DOMINATED SORTING

Suppose the individual number of the current iteration P_t is N. Generate Q_t through serious genetic operations, that is $|Q_t| = N$. The parent and child populations are combined as $R_t = P_t \cup Q_t$. Sort non-dominated R_t and divide it into multiple non-dominated levels ($F_1, F_2, \ldots$). Individuals in each non-dominated level are added into S_t one by one according to the level number until $|S_t| \geq N$. The last non-dominated level that joins S_t is denoted as F_l, and the solution set that does not contain the F_l layer is denoted as $P_{t+1} = S_t/F_l$.

B. REFERENCE POINT GENERATION

NSGA-III uses an individual selection mechanism based on reference points to maintain population diversity. Reference points can be generated according to existing structured methods, or can be set according to user preferences. The commonly used orthogonal boundary crossing algorithm proposed by Das *et al* [38].

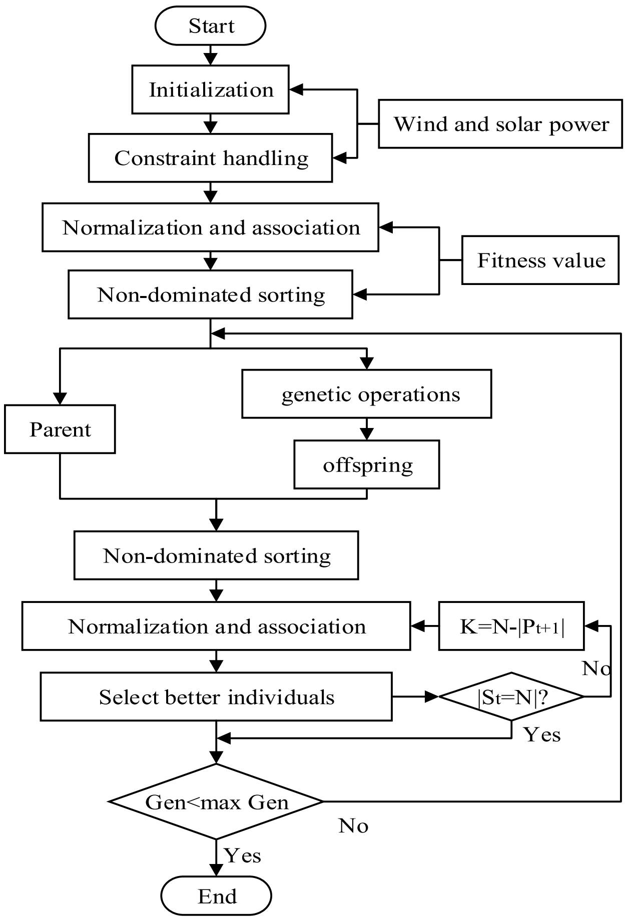

FIGURE 1. **Procedure of NSGA-III.**

C. EXTREME POINT SELECTION AND NORMALIZATION

Find the extreme point in the solution space to construct the limit plane. The distance between intersections and the ideal point is the intercept of each target axis, in which the intersections are the common point of the limit plane and each target axis. Then the target values of all dimensions with individuals are divided in the population by the intercept of the corresponding target axis to complete the individual normalization, the formulation can be denoted as,

$$g_i^N(p_j) = \frac{g_i'(p_j)}{a_i} = \frac{g_i(p_j) - g_{i,min}}{a_i} \tag{12}$$

D. LINK THE INDIVIDUALS TO THE REFERENCE POINTS

Connect the reference points with ideal points which defines a cluster of reference lines. Calculate the distance from the normalized individuals to each reference lines, where the individuals to the reference point which belongs to the reference line it the closest to the individual.

E. SELECT INDIVIDUALS

As it can be seen from Section III-A, $K = N - |P_{t+1}|$ individuals need to be selected from the F_l layer and put into P_{t+1} to obtain a new parent population P_{t+1} containing N individuals. First, the number of individuals associated with all reference points is calculated, and the number of individuals associated with the $j - th$ reference point (that is, the niche of the reference point) is recorded as ρ_j. The set $J_{min} = j : argmin_j \rho_j$ is the collection of reference points with the smallest ρ_j. When selecting individuals from F_l, if there are multiple reference points in J_min, a j_R is randomly selected to participate in the selection operation. When $\rho_{j_R} = 0$, that is, no individual in P_{t+1} is associated with the current reference point, F_l may have one or more individuals associated with the reference point, select the closest individual to j_R and put it in P_{t+1}, the niche of the reference point plus 1. If no individual in F_l is associated with j_R, replace the reference point and repeat the above steps. When $\rho_{j_R} = 0 \geq 1$, if an individual in F_l is associated with j_R, put it in P_{t+1}, add 1 to the niche of the reference point, and repeat the above steps until $|P_t + 1| = N$.

IV. NSGA-III FOR LCMOUC PROBLEM

In this section, NSGA-III is tailored for solving the proposed LCMOUC problem. In addition, the constraints in the proposed LCMOUC problem should be handled. In this section, the process of constraints handling and the application of NSGA-III for UC problem are demonstrated.

A. CONSTRAINTS HANDLING PROCESS

After initialization, the population will check the constraints. For constraint (1), a lambda iteration [39] is used. What is more, the lambda iteration is also used for constraint (4) as the upper and lower bound. For handling the reserve limit, a heuristic-based approach in literature [40] is used. If the total generation power is larger than the total load, some units should be turned off, otherwise turned on. In order to check whether the state of individuals meet constraint (3), a technique in [41] will work once violation occurs to make the individual meet the minimum up/down-time limit.

B. APPLIED NSGA-III TO LCMOUC

In addition to the constraints handling, the best individuals and objectives are to be found by NSGA-III to determine the state of units. The procedure of NSGA-III can be summarized as follows:

1) INITIALIZATION

(1) Set the parameters of the system such as the reserve rate, the total load, the minimum up/down time of each unit, and the wind/solar power generation etc.;

(2) Initialize the parameters of the algorithm such as mutation rate and maximum iteration time;

2) ALGORITHM PROCESS

(1) The individuals in the population are divided into several levels according to their dominant relationship. All individuals in the population are normalized and related to the reference points.

(2) Generate offspring populations through genetic operations such as selection, crossover and mutation.

TABLE 1. Parameters of units.

Parameters	Unit1	Unit2	Unit3	Unit4	Unit5	Unit6	Unit7	Unit8	Unit9	Unit10
$P_{max}(MW)$	455	455	130	130	162	80	85	55	55	55
$P_{mim}MW$	150	150	20	20	25	20	25	10	10	10
$a(\$/h)$	1000	970	700	680	450	370	480	660	665	670
$b(\$/MWh)$	16.19	17.26	16.6	16.5	19.7	22.26	27.74	25.92	27.27	27.79
$c(\$/MWh^2)$	0.00048	0.00031	0.002	0.00211	0.00398	0.00712	0.000793	0.00413	0.002221	0.00173
$\alpha_c(lb/h)$	130.00	132.00	137.70	130.00	125.00	110.00	135.00	157.00	160.00	137.70
$\beta_c(lb/MWh)$	-2.86	-2.72	-2.94	-2.35	-2.36	-2.28	-2.36	-1.29	-1.14	-2.14
$\gamma_c(lb/MWh^2)$	0.022	0.020	0.044	0.058	0.065	0.080	0.075	0.082	0.090	0.084
$\alpha_s(lb/h)$	198.33	195.34	155.15	152.26	152.26	101.43	111.87	126.62	134.15	142.26
$\beta_s(lb/MWh)$	2.06	2.09	2.14	2.25	2.11	3.45	2.62	5.18	5.38	5.40
$\gamma_s(lb/MWh^2)$	0.00019	0.00018	0.00220	0.00220	0.00210	0.00250	0.00220	0.00420	0.00540	0.00550
$MU(h)$	8	8	5	5	6	3	3	1	1	1
$MD(h)$	8	8	5	5	6	3	3	1	1	1
$SU_H(\$)$	4500	5000	550	560	900	170	260	30	30	30
$SU_C(\$)$	9000	10000	1100	1120	1800	340	520	60	60	60
initial state(h)	1	1	0	0	0	0	0	0	0	0

TABLE 2. Other parameters settings.

Parameters	Value
Reserve rate	0.1
Size of the population	30
Total generation number	800
Number of neighbour for three algorithms	20
Mutation constant	0.01

(3) Combine the parent and offspring populations, and perform operations like non-dominated sorting, individual normalization and association again.

(4) Select the next iteration from the merged population. Iterate back and forth until reaching the pre-set convergence condition, and output the Pareto optimal solution set.

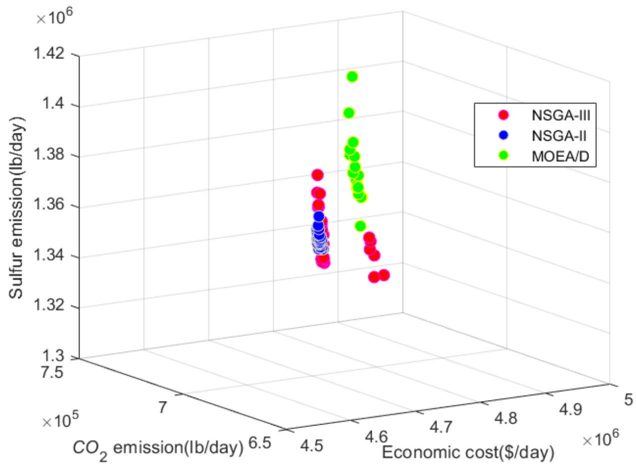

FIGURE 2. Three dimensional optimal solutions distribution.

V. NUMERICAL RESULTS AND ANALYSIS

In this section, we use the proposed algorithm to optimize the LCMOUC problem and compare the algorithm performance with NSGA-II and MOEA/D. The power system parameters used in this paper are shown in Table. 1 [42]. The emission coefficients are generated according to [43]. Other relevant parameters are shown in Table. 2. The data of wind and solar power are refer from the literature [44].

A. CASE 1: LCMOUC WITHOUT WIND AND SOLAR POWER

The optimization results of LCMOUC problem without integrating wind and solar power respectively obtained by NSGA-III, NSGA-II and MOEA/D are shown in Table. 3.

Comparing the data in Table. 3, it can be found that when the number of units is 10, the range of economic cost obtained by the NSGA-III is 568827.88\$/day-578562.55\$/day, while the optimal value obtained by the NSGA-II is 572768.11\$/day and the best result of MOEA/D is 573537.66\$/day. The target value obtained by NSGA-III is also superior to the other two algorithms. When the number of units increased to 80 and 100, the experimental data obtained by these algorithms shares the same trend. However, when only considering the economic cost or the CO_2 emission objective and the number of units is 80, the value obtained by the NSGA-II is relatively better. For example, the CO_2 emission is 652953.59 lb/day obtained by NSGA-II, the one obtained by the NSGA-III is 653959.68 lb/day, which is close to the optimal value of NSGA-II. It also shows that MOEA/D is poor in solving the CO_2 emission objective.

The three dimensional optimization results obtained by these three algorithms when the unit number is 80 are shown in Fig. 2 and two featured dimensional results are presented in Fig. 3.

From the above experimental analysis shown in Fig. 2, it can be seen that when the unit number is 80, the distribution of the Pareto front obtained by NSGA-III is smaller than that of NSGA-II and MOEA/D, and the overall Pareto solutions

TABLE 3. The results obtained by three algorithms without wind and solar power.

Unit number		Value	NSGA-III	NSGA-II	MOEA/D
10	Best	Cost($/day)	568827.88	572768.11	573537.66
		CO_2(lb/day)	81805.60	82250.07	83039.00
		Sulfur(lb/day)	153695.63	157393.14	159106.65
	Worst	Cost($/day)	578562.55	572863.85	588376.47
		CO_2(lb/day)	83809.56	82267.14	86459.26
		Sulfur(lb/day)	167085.41	157486.46	168796.67
80	Best	Cost($/day)	4560545.40	4559176.41	4749506.94
		CO_2(lb/day)	653959.68	652953.59	697706.33
		Sulfur(lb/day)	1316385.69	1367538.67	1349499.29
	Worst	Cost($/day)	4968805.91	4573500.07	4836329.73
		CO_2(lb/day)	749228.19	655263.11	718816.45
		Sulfur(lb/day)	1397783.62	1381615.58	1416464.62
100	Best	Cost($/day)	5703988.95	5700651.66	5973692.06
		CO_2(lb/day)	817832.49	816178.06	881897.29
		Sulfur(lb/day)	1647558.11	1719807.86	1679724.09
	Worst	Cost($/day)	6181477.54	5710376.22	6115647.49
		CO_2(lb/day)	931999.68	818210.35	916005.72
		Sulfur(lb/day)	1742127.88	1736856.00	1743744.83

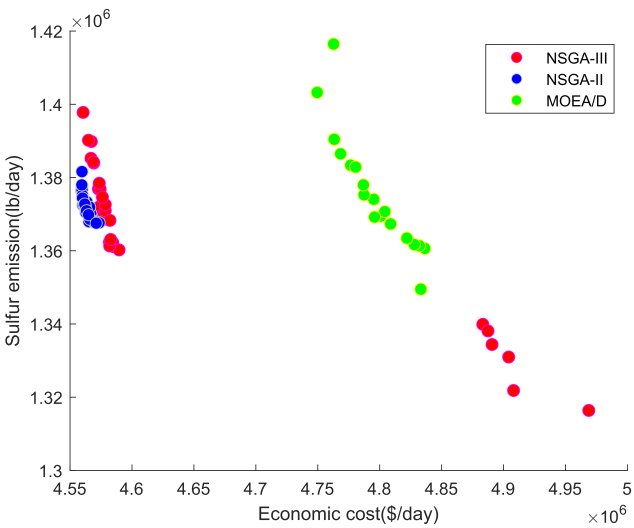

FIGURE 3. Two dimensional optimal solutions distribution.

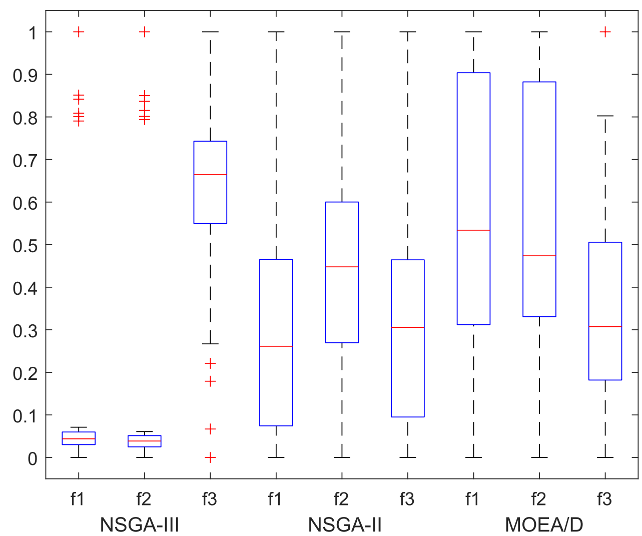

FIGURE 4. The normalization box plot for results of three algorithms.

are relatively downward. Compared with the Pareto frontier in three-dimensional space, it can be seen that the Pareto frontier of NSGA-III is at the lowest level, followed by NSGA-II, and MOEA/D is at the top. NSGA-III can get far smaller value than other algorithms, which fully shows that NSGA-III performs well in optimizing the LCMOUC problem. From Fig. 3, it could be easily found that MOEA/D performs the worst on these two objectives. Although NSGA-III gets some high value solutions, it can obtain the best solution for both the two objectives.

Considering that all the objectives have the same evaluation weight for the system, normalization and weighted sum methods are adopted to make decisions on the Pareto solution obtained by the NSGA-III. The normalization adopts the mapminmax function in Matlab(R)2019b. The normalized three objective values are weighted and summed up. The minimum value is selected as the optimal solution. It can be found that the smallest weighted sum value can meet at least two or more objectives relatively better in the Pareto frontier. Moreover, normalization box plot of these results are used to further compare these algorithms, which is shown in Fig. 4.

It could be found that the normalization values of NSGA-III are relatively small, and the values of objective $f1$ and $f2$ are even smaller than 0.1. NSGA-II performs well in $f3$, which outperforms all the other methods, but the results of $f1$ and $f2$ are worse than NSGA-III. The results of $f1$ and $f2$ obtained by MOEA/D are relatively worse than the other two algorithms, and its $f3$ value is among the middle ranking.

TABLE 4. Power of 10 units.

Hour	Unit1	Unit2	Unit3	Unit4	Unit5	Unit6	Unit7	Unit8	Unit9	Unit10
1	366.9	333.1	0	0	0	0	0	0	0	0
2	390.3	359.7	0	0	0	0	0	0	0	0
3	315.5	445.6	0	0	88.9	0	0	0	0	0
4	455	455	0	0	40	0	0	0	0	0
5	446.1	405.9	87.2	0	60.8	0	0	0	0	0
6	384.8	382.8	128.0	108.5	96.0	0	0	0	0	0
7	405.4	392.1	122.3	103.9	126.3	0	0	0	0	0
8	455	451.5	130	38.8	124.6	0	0	0	0	0
9	455	423.6	130.0	114.9	72.1	79.4	25.1	0	0	0
10	454.6	408.8	130	126.9	116.8	71.0	81.9	10	0	0
11	453.8	454.9	130	129.2	159.4	21.4	79.3	10	11.9	0
12	454.4	453.6	127.2	130	152.1	80	66.8	14.2	10.0	11.7
13	452.6	455	130	130	162	29.7	29.2	11.5	0	0
14	455	454.7	130.0	130.0	84.7	20.6	25	0	0	0
15	455	454.8	125.7	78.7	85.7	0	0	0	0	0
16	430.3	352.0	102.2	69.3	96.1	0	0	0	0	0
17	454.3	260.7	130.0	130	25	0	0	0	0	0
18	349.3	410.6	129.0	129.3	81.9	0	0	0	0	0
19	432.4	454.6	85.8	129.9	97.2	0	0	0	0	0
20	452.6	443.8	122.8	129.2	162	20	29.0	40.6	0	0
21	455	455.0	130	100.9	83.6	20	55.5	0	0	0
22	44.0	455	0	0	138.3	27.7	25	0	0	0
23	359.4	443.6	0	0	97.0	0	0	0	0	0
24	345.0	455	0	0	0	0	0	0	0	0

After the normalization and sum up, the example obtained by NSGA-III is selected for analysis when the unit number is 10. The economic cost value is 568827.88 \$/day, the CO_2 emission is 81805.60 lb/day and the sulfur emission is 167085.41 lb/day. The power of the units are shown in Table. 4. According to the data in the table, it can be seen that unit 1 and unit 2 are always on-line, while the power changes with the system load.

B. CASE 2: LCMOUC WITH WIND AND SOLAR POWER

In addition to the non-renewable case, the optimization results of LCMOUC problem integrating both wind and solar power are obtained by NSGA-III. The numerical study has also compared the results obtained by NSGA-II and MOEA/D shown in Table. 5.

It can be found that when the number of units is 10, and the range of economic cost obtained by the NSGA-III is 549649.33 \$/day-557719.37 \$/day. The optimal value obtained by the NSGA-II is 550624.12 \$/day, whereas the one of MOEA/D is 550598.45 \$/day. The target value obtained by NSGA-III is also superior to the other two algorithms when integrating wind and solar power. When the number of units increased to 80 and 100, the experimental data obtained by these algorithms are seen the same ranking. However, when the number of units is 100, the economic cost and CO_2 emission value obtained by the NSGA-II is relatively better. For example, the CO_2 emission value is 778713.29 lb/day obtained by NSGA-II, the one obtained by the NSGA-III is 779727.42 lb/day, which is close to the optimal value of NSGA-II. It is obvious that the majority of the results obtained by NSGA-III are better than other counterparts.

Comparing with the data in Table. 3, it can be found that after integrating wind and solar power to the power system, whatever the unit number is, the optimization value of these three objectives are all smaller than that of the case without integrating wind and solar power, which means that wind and solar power can decrease the total economic cost of the power system and are environmentally friendly to release less pollutant emission. For example, when the unit number is 100, the economic cost obtained by NSGA-III is 5703988.95 \$/day, the CO_2 emission value is 817832.49 lb/day and the sulfur emission value is 1647558.11 lb/day when there are no wind and solar power in the system. When the power system integrates wind and solar power, the economic cost is 5484988.47 \$/day, the CO_2 emission value is 779727.442 lb/day and the sulfur emission value is 1597417.77 lb/day. It can clearly see that all the three objective values are lower than that of the system with no wind and solar power, which can obviously show the advantages of wind and solar power in reducing economic cost and pollutant emission. The three dimensional optimization results integrating wind and solar power obtained by these three algorithms of 80 units are shown in Fig. 5 and two featured dimensional results are presented in Fig. 6.

TABLE 5. The results obtained by three algorithms integrating wind and solar power.

Unit numer		Value	NSGA-III	NSGA-II	MOEA/D
10	Best	Cost($/day)	549649.33	550624.12	550598.45
		CO_2(lb/day)	78454.40	78487.70	79198.26
		Sulfur(lb/day)	149118.27	154626.83	154071.29
	Worst	Cost($/day)	557719.37	550726.33	563612.98
		CO_2(lb/day)	79761.59	78498.74	82048.12
		Sulfur(lb/day)	159725.13	154732.90	166808.63
80	Best	Cost($/day)	4387781.40	4388337.30	4588342.48
		CO_2(lb/day)	623615.98	623747.53	669029.28
		Sulfur(lb/day)	1274974.56	1327095.93	1297519.13
	Worst	Cost($/day)	4783209.21	4397241.38	4782472.63
		CO_2(lb/day)	716844.98	625000.61	715348.46
		Sulfur(lb/day)	1355160.33	1344159.27	1376333.81
100	Best	Cost($/day)	5484988.47	5482424.81	5758271.31
		CO_2(lb/day)	779727.42	778713.29	840167.63
		Sulfur(lb/day)	1597417.77	1664866.87	1611497.46
	Worst	Cost($/day)	6005646.12	5492809.35	5982291.48
		CO_2(lb/day)	903548.38	780998.58	895152.60
		Sulfur(lb/day)	1699831.64	1682536.38	1724665.96

TABLE 6. Power of 10 units when integrating wind and solar power.

Hour	Unit1	Unit2	Unit3	Unit4	Unit5	Unit6	Unit7	Unit8	Unit9	Unit10
1	322.7	366.7	0	0	0	0	0	0	0	0
2	283.6	444.1	0	0	0	0	0	0	0	0
3	370.6	453.9	0	0		0	0	0	0	0
4	378.1	436.5	0	0	109.9	0	0	0	0	0
5	430.0	452.4	0	0	92.2	0	0	0	0	0
6	430.1	455	100.0	0	89.4	0	0	0	0	0
7	403.2	380.1	130	130	81.1	0	0	0	0	0
8	453.9	414.5	122.6	130	36.0	0	0	0	0	0
9	392.8	409.4	130.0	130	109.5	0	71.4	0	0	0
10	391.9	407.4	130	129.7	160.9	34.1	84.5	0	0	0
11	454.3	454.9	130	130.0	146.9	34.5	25.8	10.0	0	0
12	453.2	442.3	130.0	128.5	124.9	69.4	67.1	13.11	10.0	0
13	455	443.3	129.3	130	135.0	20	25.0	0	0	0
14	447.2	395.6	129.0	111.0	99.5	0	61.3	0	0	0
15	427.0	388.0	130.0	130	94.7	0	0	0	0	0
16	452.2	356.0	108.0	81.2	25	0	0	0	0	0
17	282.7	455	129.1	64.4	43.3	0	0	0	0	0
18	374.5	374.3	109.4	106.8	115.9	0	0	0	0	0
19	419.3	446.0	126.1	58.0	125.0	0	0	0	0	0
20	417.3	450.6	130	130.0	157.6	22.2	27.8	46.5	0	0
21	376.6	444.9	92.5	130	109.9	35.6	85	0	0	0
22	451.5	418.8	0	0	125.1	20.1	63.0	0	0	0
23	346.4	449.7	0	0	103.9	0	0	0	0	0
24	375.3	422.2	0	0	0	0	0	0	0	0

Comparing Fig. 2 and Fig. 3 with Fig. 5 and Fig. 6, it can be seen that the distribution results of the three algorithms for UC integrating wind and solar power are similar to that of case 1. Whether the LCMOUC integrates the wind and solar power or not, the Pareto frontier of NSGA-III is always at the lowest level, which verifies that NSGA-III is suitable for solving LCMOUC problem again. In addition, normalization box plot of these results are again sused to further compare these algorithms, which is shown in Fig. 7.

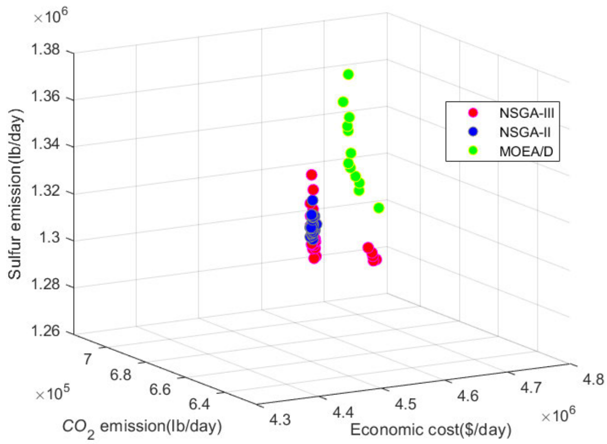

FIGURE 5. Three dimensional optimal solutions distribution.

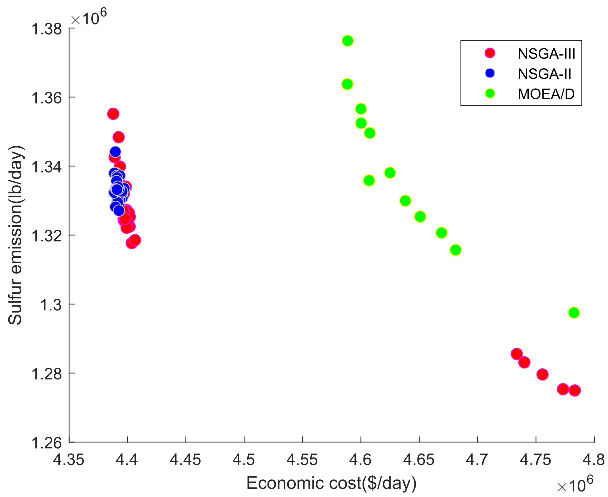

FIGURE 6. Two dimensional optimal solutions distribution.

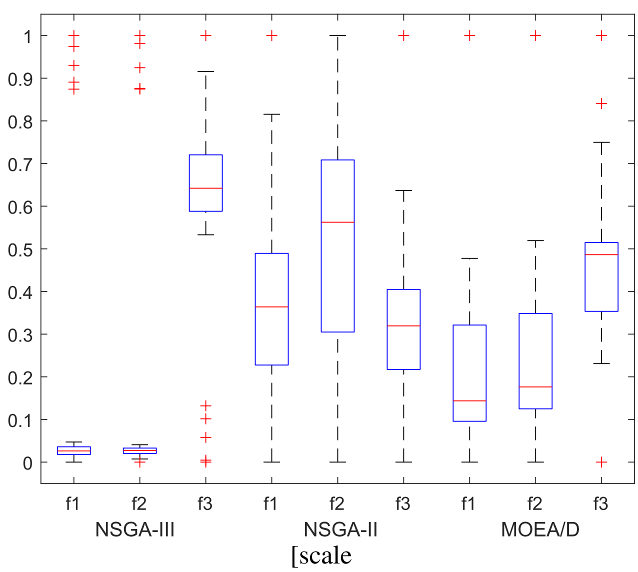

FIGURE 7. The normalization box plot for results of three algorithms.

It could be found that all the results are relatively smaller than that when the power system does not integrate wind and solar power, and the value $f1$ and $f2$ of NSGA-III are lower than 0.05. NSGA-II performs well again in $f3$ while the result of $f2$ is the worst in these three algorithms. The results of $f1$ and $f2$ for MOEA/D are both better than NSGA-II.

After the normalization and sum up, the best solution obtained by NSGA-III of 10 unit is selected for analysis. The economic cost is 551277.94 \$/day, while the CO_2 emission is 78629.93 lb/day and the sulfur emission is 158042.88 lb/day. The power of the units are shown in Table. 6. According to the data in the table, it can be seen that unit 1 and unit 2 are always on, while the power changes with the system load. Unit 10 is always off, which means that the system does not need all the units work to meet the demand when integrating wind and solar power, thus decreasing the economic cost and pollutant emission.

VI. CONCLUSION

In this paper, a low carbon multi-objective unit commitment model is formulated combining CO_2 emission and environmental objectives on the basis of original UC problem in the power system operation. The competitive NSGA-III algorithm is employed for solving the proposed LCMOUC problem. Two featured cases with and without renewable energy generations are used to verify the applicability of NSGA-III, and two other counterparts NSGA-II and MOEA/D are adopted in the comparison. It can be found that NSGA-III can obtain the best solution compared to the other two algorithms whether the power system integrating wind and solar power or not. The normalization method is used to make a decision on the Pareto frontier, where NSGA-III can almost achieve the optimal economic and environmental value for all the different situations. The carbon emission is also significantly reduced by utilizing the proposed model framework and algorithm solutions. In the future, more available low carbon options including plug-in electric vehicles and energy storage systems are to be integrated in the unit commitment problem, further integrating the intermittent renewables and reducing carbon emissions.

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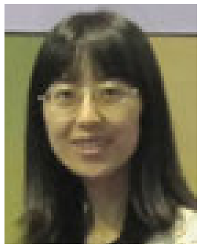

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